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Temporal Dynamics of Willingness to Pay for Alternatives that Increase the Reliability of Water and Wastewater Service

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Temporal Dynamics of Willingness to Pay for Alternatives that Increase the Reliability of Water and Wastewater Service

by

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Dedication

To my family, for their unwavering support and encouragement on the journey to this milestone. Especially my mother, who was hesitant about the idea that her son was going to be 2000 miles away (and may end up starving himself), but still pushed me to pursue a Master's degree. To my friends for the constant laughter which allowed me to mentally step away from long days. Finally, to Erica, for being the most amazing human being.

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Abstract

Temporal Dynamics of Willingness to Pay for Alternatives that Increase the Reliability of Water and Wastewater Service

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Public perceptions are dynamic and, continually being in flux, they can profoundly impact infrastructure projects and policies. Providers of water and wastewater services need to understand the dynamic nature of public perceptions so as to be able to identify times of greater public support. They may thus be able to take timely actions to implement capital projects or increase operational revenues. In this study, the dynamic nature of public perceptions is demonstrated through survey analyses of data collected, between 2013 and 2016, in 21 shrinking U.S. cities. A random-parameters Tobit regression model identified influential geographic and sociodemographic factors that changed over time on user stated willingness to pay (WTP). A likelihood ratio test confirmed a statistically significant shift, between 2013 and 2016, in participants' WTP values. Model results reveal that, between the timeframes of the deployed surveys, the influences of geographic (e.g., Michigan and Ohio) and sociodemographic (e.g., age, income) factors on stated WTP did in fact change. The influential parameters that indicate greater public support can be leveraged by infrastructure managers to develop strategies that may result in the successful delivery of infrastructure projects and that increase operational revenues.

Moreover, public perceptions should be periodically investigated to continually identify times of greater public support for infrastructure projects.

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INTRODUCTION

Public perceptions change with time, new information, and events (Krewski et al. 2006; Li et al. 2015). This dynamic nature of public perceptions of a project can have cascading effects on the implementation of infrastructure projects, sometimes even halting them. For example, the construction of the Keystone Pipeline was delayed in 2015 due to public disapproval, but was later approved with public support in 2017 (DiChristopher 2017). Across the U.S., public opposition has halted other projects, such as the Glades Reservoir project in Northern Georgia (Bowman 2017) and a housing development in San Francisco's Mission District (Waxmann 2015).

Beyond halting the implementation of physical projects, the temporal characteristics of public opinion can also have an impact on infrastructure policies (Lorenzoni et al. 2007; West et al. 2010; Leung et al. 2013). Changing public opinion, for instance, affects the policy of privatizing critical infrastructures (Hall et al. 2014). Voters in Atlanta, Georgia, for example, passed a measure to privatize their water systems, only to later reject the decision once public perceptions shifted (Jehl 2003). In addition to affecting infrastructure projects and policies, the consequences of shifting perceptions can also influence the public's willingness to pay (WTP) for infrastructure projects.

Indeed, when it comes to implementing project alternatives and policies, an important factor in the success of such endeavors is public WTP for infrastructure projects. Scholars define WTP as the stated amount that a consumer is willing to pay for specific goods or services. In 2016 voters in Portland, OR, for example, approved a four-year gas tax (10 cents per gallon) to pay for road infrastructure improvements. The measure was supported by businesses, neighborhood associations, and teachers (Njus 2016). The proposed tax is projected to raise, over this four-year period, $64 million to pay for road repairs as well as pedestrian and bicyclist safety improvements (Njus 2016). Similarly, residents of Oklahoma City, OK, approved an increase to their sales tax as part of an effort to improve their city's infrastructure (Querry 2017). This fund, which is expected to generate $240 million over 27 months, will allocate $168 million to street resurfacing, $24 million to street enhancements, $24 million to new sidewalks, $12 million to new trails, and $12 million to a new bicycle infrastructure (Querry 2017). In literature, Rollins et al. (1997) found that consumers were willing to pay an additional $26 each month for improved water services in Canada if the result was perceived improvements. This would generate an additional revenue of $3.5 billion annually for Canadian Public Utilities to employ at their discretion (Rollins et al. 1997). Given its possible impact on WTP, the dynamic nature of public perceptions need to be understood, as it can be critical to project execution. Capturing these public perceptions during times of support for projects can result in significant project revenue.

As noted by Flyvberg et al. (2004), the average lifespan of an infrastructure project is 13 years. During which time, public perceptions toward infrastructure alternatives, levels of service, and WTP are, due to the ephemeral nature of public views, likely to shift. Indeed, the public can turn against a project due to external factors such as proximity to events in similar cities, negative media coverage, and the economic state of a community (Valentin and Bogus 2012; Naderpajouh et al. 2014). Researchers often try to capture these perceptions using cross-sectional methods (e.g., semi-structured interviews, focus groups, surveys) (e.g., Taylor et al. 2012; Ma et al. 2015; Lewis et al. 2017). Such methods capture, however, the publics' perception only at a specific period; they cannot assess public reaction to certain events that may arise or provide decision makers up-to-date information (Li et al. 2015; Whittington et al. 1990). For instance, a cross-sectional examination of public perceptions towards the construction of the Keystone Pipeline in 2015 revealed widespread disapproval of the project (DiChristopher 2017). By 2017, however, the political climate had altered and the public generally approved of the project (to be under construction in January of 2019) (DiChristopher 2017).

As for the Glades Project, when the media began to report that drought conditions were no longer a threat to Georgia, public sentiment turned to disapproval of an initial $16 million planning investment (Bowman 2017). Portland experienced rather the reverse for its transportation projects. Lawmakers failed early on to pass taxes supporting transportation infrastructure (in Portland in 2015) only to succeed eventually thanks to shifting public perceptions (Njus 2016). People at different geographic locations and from across sociodemographic groups can, as noted above, have their perceptions variously influenced by such external factors as proximity to events and negative media coverage (Faust et al. 2016a; Osman and Faust 2017). Consequentially, the periodic assessment of public perceptions aids decision makers as they try to gauge any shift in support and opposition.

In addition to cross-sectional assessments, researchers have applied other survey analysis techniques to consumer-stated WTP to gain insights into users' perceptions of the value that these services provide. Such techniques have included contingent valuation methods (CVM), which is an economic valuation of a non-marketed good (Rollins et al., 1997), to gauge users' WTP for water infrastructure investments (e.g., Rollins et al. 1997; Fujita et al. 2005; Hensher et al. 2005; Alcubilla and Lund 2006; Banda et al. 2007; Genius et al. 2008; Lewis et al. 2017). These studies have validated the use of CVM on assessing public WTP for infrastructure services, identifying the factors that influence this perception. Banda (2007) applied CVM to estimate South African residents' WTP for quantity and quality of water when there existed no standard price on the quantity and quality of water. With the residents of Iquitos, Peru, Fujita (2005) used CVM to measure their WTP for water and sanitation services and to establish tariffs for these services. In 2002 in Canberra, Australia, Hensher et al. (2005) deployed a stated preference survey to 211 households that listed choices between differing services and their respective prices. The results from these studies support the idea that residents put a monetary value on water services reliability; this is further verified by their associating a greater WTP for reduced service interruptions (Hensher et al 2005). WTP data collected in Crete by Genius et al. (2008) found that residents were willing to pay a 17.6% increase in their bill for improvements to the water and wastewater quality. These studies show through several different examples the applicability of CVM to measuring end-user WTP for water and wastewater services.

Although WTP studies have shed light on factors that influence the stated WTP, they often yield a high proportion of zeros (Hensher et al. 2005; Genius et al. 2008; Veronesi et al. 2014; Faust et al. 2016; Faust et al. 2018). Notably, a challenge to CVM is differentiating between “true” and “protest” zeros. “True” zeros represent a completely valueless amenity to the respondent, while “protest” zeros represent respondents’ rejection to a portion of the amenity or a respondent’s perception that another entity should be responsible for the amenity (Lindsey 1994; Fonta et al. 2010; Tentes and Damigos 2015). Previous studies have overcome this challenge by coupling CVM with certain statistical methods, for example, the full information maximum likelihood estimator (Fonta et al. 2010), the four-hurdle model (Yu and Abler 2010), and discrete response logit models (Hanemann 1984). Expanding on the combination of statistical modeling and CVM, researchers have also used the Tobit regression procedure for overcoming large numbers of zero responses (Bowker et al. 2003; Cho et al. 2008). Hoon et al. (2008) noted that Tobit models accounted for the bias induced by true zero and protest zero responses concerning respondents’ stated WTP for land conservation easements in North Carolina.

Of particular interest to this study are individuals’ WTP for improved water and wastewater level of service (LOS) reliability—defined as uninterrupted, clean water at an adequate pressure—in U.S. shrinking cities. Shrinking cities are defined as medium and large cities that have, over multiple decades, experienced chronic urban decline of at least

30% or more after a population peak of approximately 100,000 persons or more. This subset of public perceptions, stated WTP, is assessed on residents of shrinking cities as the physical footprint of the infrastructure systems are much greater, due to the large-peak populations, than that needed to support the non-uniform population across the city. This non-uniform population causes many operational and quality challenges to both utility providers and end-users, such as, high water ages, stagnant water, and settlement of solids within wastewater system (Faust et al. 2016b). Additionally, due to declining populations and the consequent decreasing number of users on systems, per capita costs for infrastructure services increase (Faust et al. 2016b). The burden of the increased costs of maintaining and operating the high fixed-cost systems typically fall on those least equipped to shoulder such burdens, for indeed the urban decline results in higher poverty rates (Pallagst 2009; Faust et al. 2016b).

The operating environment of shrinking cities—underutilized systems and reactive maintenance—gives rise to a reduced LOS provided to users (Faust et al. 2016b). Several studies have shown, though, that those of lower income are willing to pay for improved goods and services (Knetsch 1990; Whittington et al. 1990; Faust et al. 2016b; Faust et al. 2018). Faust et al. (2016) found that in 2013 residents in shrinking cities were willing to pay increased rates if it resulted in perceived increases in their water and wastewater levels of service. In cities of other classifications (i.e., outside of shrinking cities), Whittington et al. (1990) found that residents in a rural Haitian city were willing to pay more for improved water services, despite annual household incomes being approximately US$800. These findings suggest that incorporating public perceptions into the decision-making process can result in increased functioning revenues (in this case, increasing rates for improved levels of service) for utilities and project managers. Similar to the cases in Portland and Oklahoma City where the public perceived the current city transportation infrastructure as inadequate, the public supported gas and sales tax increases for capital projects and future infrastructure investments (Njus 2016; Querry 2017). This finding underscores the idea that public perceptions are dynamic and that the success of infrastructure projects can depend on capturing them at specific times.

This study seeks to accomplish three objectives. It seeks to: (1) assess the temporal dynamics of public perceptions with regards to WTP for the improved LOS reliability of their water and wastewater systems between 2013 and 2016 in which water sector infrastructure were brought to the forefront of media discussions; (2) present a methodological approach to evaluate the drivers of WTP; and (3) discuss the implications that stated WTP and accompanying drivers may have on the provision of water and wastewater services and infrastructure projects. The results of this study fulfill a need in the literature and in practice to understand the temporal characteristics of WTP as well as the attendant geographic and demographic drivers. In fact, this study aims to show how the geographic and demographic drivers of public perceptions are susceptible to exogenous factors (e.g., proximity to events, policy changes) within the cities or nearby areas. Understanding the demographic drivers provides an opportunity for decision makers (e.g., utilities) to tailor outreach methods to gain public approval of infrastructure alternatives.

Additionally, understanding the geographic drivers can assist in capturing public approval of infrastructure improvement projects through stated WTP, which can enable the implementation of infrastructure projects in communities that would otherwise oppose these projects.

METHODOLOGY

Survey Development and Deployment

In 2013, a survey was deployed in 21 U.S. shrinking cities to assess public perceptions of water and wastewater infrastructure service received and of alternatives implemented across the cities. The survey included questions to capture the public's attitudes, awareness, and understanding of water and wastewater infrastructure challenges within their city, including questions regarding possible retooling alternatives. Retooling alternatives refer to changes to the systems that are either physical, operational, or managerial, intended to reduce the footprint of the infrastructures to align more closely with that needed by the current population (e.g. decommissioning components, repurposing components) (Faust et al. 2015). Of interest to this study are the survey questions pertaining to the water quality received at the tap and the stated WTP for improved water and wastewater service (specific questions shown below). Between the time of the original survey (2013) and 2016, the media increased its attention to water sector infrastructure issues nationwide (e.g. Schwirtz 2013; Satija 2014; FEMA 2013; CNN Library 2017). As a result, in 2016 researchers deployed to the same cities a second survey, one that included questions from the initial survey and new questions as well. These shrinking cities consisted of the following: Akron, OH; Baltimore, MD; Birmingham, AL; Buffalo, NY; Camden, NJ; Canton, OH; Cincinnati, OH; Cleveland, OH; Dayton, OH; Detroit, MI; Flint, MI; Gary, IN; Niagara Falls, NY; Pittsburgh, PA; Rochester, NY; Saginaw, MI; Scranton, PA; St. Louis, MO; Syracuse, NY; Trenton, NJ; and Youngstown, OH (see Figure 1).

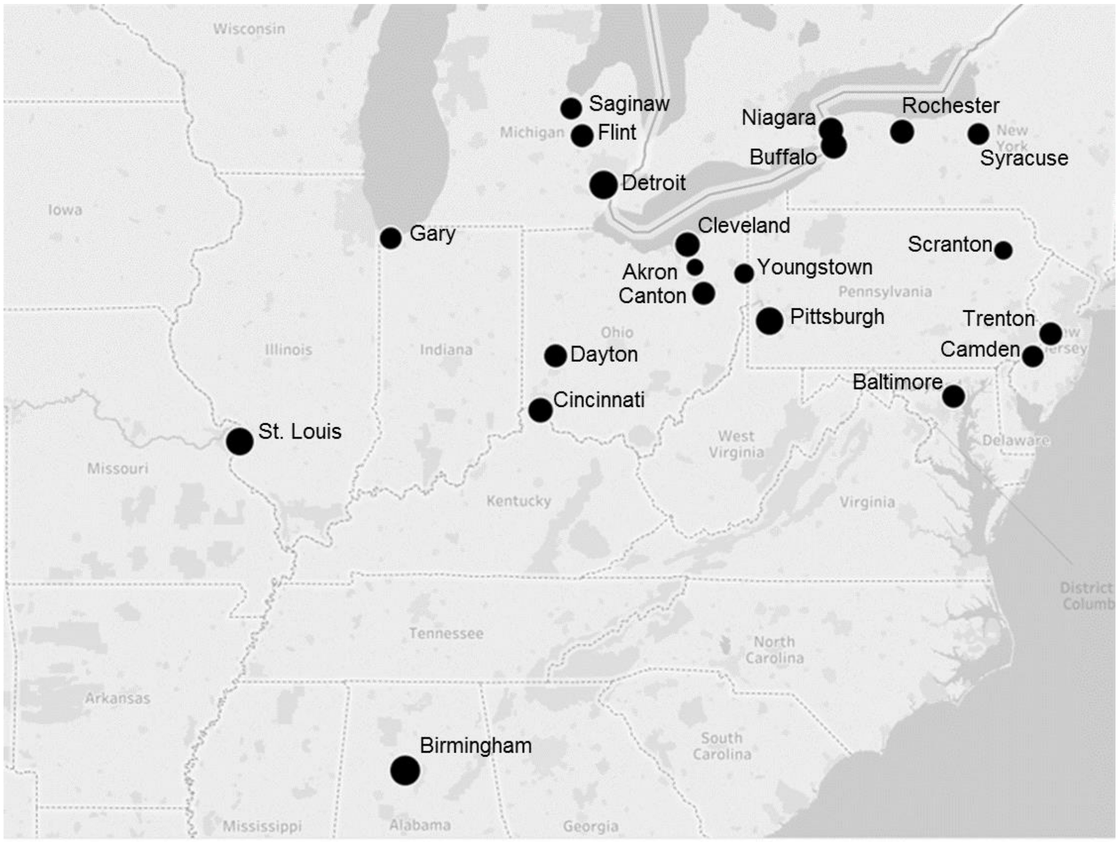


Figure 1. Geographic distribution of survey respondents in shrinking U.S. cities (size is indicative of relative number of responses from respective cities)

Prior to distribution, researchers obtained approval from the Institutional Review Board (IRB) both surveys, which were also reviewed by more than 10 subject matter experts (SMEs) in the fields of survey analyses, water infrastructure, shrinking cities, or a combination thereof. Each survey was pre-deployed to 25 individuals. This was done to assess how difficult the survey was to understand and to ensure that it was capturing the intended data. The final sample excludes the pre-deployment responses. Once finalized, survey participants were identified via random sampling by Qualtrics, LLC, utilizing geographic quotas (Qualtrics 2016). All respondents voluntarily completed the surveys and were at least 18 years of age. To ensure that the sample adequately resembled the sociodemographic conditions of shrinking cities, researchers used the primary demographic of income (see Table 1). Based on the 2016 national poverty average, poverty rates in shrinking cities were more than double the national poverty rate of 12.7% (Semega et al. 2017). For instance, the 2016 American Community Survey 1-Year Estimates reported that Detroit, MI; Gary, IN; and Cleveland, OH; had poverty rates 35.7%, 33.3%, and 35.0% (U.S. Census Bureau 2016). Of the 839 surveys from 2013 and the 979 surveys from 2016, 421 and 451 valid responses were received, providing a 95% confidence (+/-5% margin of error).

In this study, researchers assess two questions of interest pertaining to WTP, specifically:

> *How much more would you be willing to pay for improved reliability of you water (wastewater) service? (percent increase in current water [wastewater] bill)*

The survey defined LOS reliability as the *perceived* improved quality (e.g., water quality received or reduced combined sewer overflows) or operational characteristics (e.g., fire flows, pressures, reduced disruption of service) associated with the level of service provided; definition of terms provided in the surveys. Respondents willing to pay for increased water and wastewater rates could either enter their desired percentage via direct text entry or move a slide bar to their desired value. Opting out of the question did not, as noted above, default to zero. With WTP surveys, it is common to see respondents report WTP values of zeroes as shown in Figure 2 below(Hensher et al. 2005; Genius et al. 2008; Veronesi et al. 2014; Faust et al. 2016c). While these zero values provide significant information to understanding WTP factors, they may consist of “protest” zeros. “Protest” zero responses occur when an individual values the proposed change, but holds an aversion to some component of the change, such as the payment mechanism or the entity managing the change. The aversion to any aspect of the program results in “protest beliefs” in individuals, who respond to WTP questions with a protest-zero (Jorgensen and Syme 2000). To avoid the issue of omitted variable bias, the survey tool required respondents to enter “0” if they were not willing to pay for improved water and wastewater LOS reliability. By requiring that they enter the 0, the protested amount (skipping the question) could be separated from the entered amount and used in the statistical analyses (Sudman et al. 1989). In this study, protest zeros are treated as legitimate zeros, as respondents are valuing a policy rather than a commodity (Halstead et al. 1992). Addressing protest zeros is necessary to ensure that neither the true mean WTP is reduced or sample selection bias occurs (Halstead et al. 1992; Strazzera et al. 2003; Faust et al. 2018).

Surveys, while providing useful information on individual’s perceptions and behaviors, have inherent limitations that pose modeling and interpretation challenges (Faust et al. 2018). Survey instruments do not capture all possible factors influencing an individual’s decision or perception regarding certain activities, such as WTP. Thus many factors, such as lifestyle characteristics, escape observation, potentially giving rise to model specification errors, (e.g., omitted variables, and erroneous inferences and predictions; Mannering et al. 2016).

The purpose of this study is to measure the stated WTP of residents in shrinking cities to demonstrate how public perceptions, and their drivers, can change over time. The deployment of the survey to medium and large U.S. shrinking cities may limit the application of the results to that sort of city. Additionally, since the questions of this study focus on public perceptions towards the WTP for improved water and wastewater LOS reliability, this study only assesses the influence of water sector-related events, such as the Flint Water Crisis and Superstorm Sandy, as possible explanations for the shift in public perceptions. Other events, such as those not directly related to water-sector infrastructure (e.g., distrust in public officials), may have influenced the temporal dynamics of public opinions during this time span and should be considered as possible causes. Further, public perceptions regarding water sector infrastructure may have been altered by events occurring after the 2016 survey and are thus not accounted for in this study. Despite these limitations, the results of this study can be used for targeted outreach programs to enhance public support and create sustainable infrastructure solutions and alternatives.

Econometric Modeling

Previous WTP studies have utilized the finite mixture, or latent class approach, to account for unobserved heterogeneity and address issues associated with statistical modeling and survey analysis (Beharry-Borg and Scarpa 2010; Cooper et al. 2018; Faust et al. 2018). The latent class estimation approach accounts for unobserved heterogeneity by classifying observations into distinct classes based on similar characteristics. One drawback to this approach is that the number of classes are usually small and results in a coarse approximation of the distribution of heterogeneity (Behnood 2014; Pahukula et al. 2015). Additionally, the latent class approach does not account for variation within a class by assuming parameter homogeneity within each class (Pahukula et al. 2015; Mannering et al. 2016). Faust et al. (2018) used such latent class methods for the estimation of WTP. Considering the geographic parameters proposed in this study, it was found that a better fit was achieved using alternative models that, extending beyond the sole consideration of sociodemographic parameters, captured more unobserved heterogeneity. Thus, the random-parameter method is proposed.

The random-parameter modeling approach accounts for more unobserved heterogeneity by allowing estimated parameters to vary across observations (i.e., individuals in this study) according to a user-defined distribution, such as normal, lognormal, triangular, or uniform distributions, rather than distinct classes (Mannering et al. 2016). This methodology is more suitable in statistical analyses involving parameters that contain considerable variation across each observation, such as city-, state-, or regional-level parameters. Incorporating these parameters and accounting for their variation will provide more meaningful results.

To expand on the applicability of heterogeneity-based approaches on WTP analyses and account for more unobserved heterogeneity, the present study utilizes a random-parameter modeling approach. Censoring WTP values at zero, we apply the random-parameter method to the Tobit regression modeling approach (Tobin 1958) to account for the high proportion of zero values and potential protest zeros typically found in WTP studies (Faust et al. 2018). This methodology helps correctly identify and understand the geographical and sociodemographic factors that influence an individual's WTP for increased water and wastewater rates. Furthermore, this study assesses the temporal aspect (2013 vs. 2016) of these geographical and sociodemographic parameters.

By censoring the analysis at a given value, in this case at zero WTP (see Figure 2), Tobit regression can, without omitting observations, account for the skewed nature (distribution) of this WTP data for improved water and wastewater LOS reliability (Faust et al. 2018). The Tobit model alone, however, does not account for any unobserved heterogeneity that innately exists with stated preference surveys. As such, heterogeneity-based extensions must be applied to ensure accurate parameter estimates and inferences. Past WTP studies have, as noted above, applied the latent class approach to account for this unobserved heterogeneity in WTP survey data. Doing so, though, does not allow parameters to vary within each class, limiting the inclusion of certain variables that can vary greatly (e.g., geographic parameters). To incorporate factors that vary more than others, the random-parameter method is applied to the Tobit model to ensure accurate parameter estimates and inferences. This extension of the Tobit modeling captures more unobserved heterogeneity within the two surveys by allowing estimated parameters to vary across individuals rather than across groups of observations (Mannering et al. 2016). The sections that follow detail both the random-parameter extension of the Tobit regression model used in this work and the goodness-of-fit measures used to assess model significance.

In this study, the standard Tobit regression model is extended to the random-parameter modeling framework. The standard Tobit regression model is able to left-censor the data at a value corresponding to the WTP and account for the aggregation of responses at zero (see Figure 2). If traditional linear regression models were used, the analysis would ignore this feature of the data set and would underestimate the response of WTP to the covariates (Greene 2012). The standard Tobit model is formulated as follows (Tobin 1958):

$$Y_i^* = \boldsymbol{\beta X_i} + \varepsilon_i \; with \; \varepsilon_i \sim N[N, \sigma^2] \; and \; i = 1,2, \dots N \tag{1}$$

Where:
$Y_i = Y_i^* \; if \; Y_i^* > 0$
$Y_i = 0 \; if \; Y_i^* \leq 0$

, where N is the number of observations, Y_i is the WTP (the response parameter) of observation i for improved water or wastewater LOS reliability, $\boldsymbol{X_i}$ is the vector of explanatory parameters (geographic and sociodemographic characteristics), $\boldsymbol{\beta}$ is the vector of estimated parameters, and ε_i is the normally and independently distributed error term with a mean of zero and constant variance, σ^2. The Tobit regression model is estimated by maximum likelihood estimation procedures (see Green 2012; Brown et al. 2015).

The deployed surveys provide adequate information regarding individuals' perceptions of WTP for water and wastewater services. They are incapable, though, of capturing all possible factors that may influence an individuals' WTP. Ignoring both this unobserved heterogeneity and variation across the parameters leads to inaccurate estimates and erroneous inferences (Mannering et al. 2016). To account for the unobserved heterogeneity, the standard Tobit regression model is extended to employ the random-parameter modeling framework. The random-parameter modeling framework captures this unobserved heterogeneity through the Tobit framework by allowing estimated parameters to vary across observations. The random parameter is written as follows (Greene 2012):

$$\beta_i = \beta + \phi_i \tag{2}$$

, where the log-likelihood function is (Brown et al. 2015):

$$logL = \sum_{\forall i} ln \int_{\phi_i} g(\phi_i) P(Y_i^* | \phi_i) d\phi_i \tag{3}$$

, and $\mathrm{g}(\phi_\mathrm{i})$ is the probability density function of ϕ_i and $\mathrm{P}(\mathrm{Y}_\mathrm{i}^* | \phi_\mathrm{i})$ is the probability of the Tobit model being censored or uncensored. The probability density function, $\mathrm{g}(\phi_\mathrm{i})$, is conditional on a distribution (e.g., normal, triangular, uniform) that is specified by the analyst (Green 2016). The chosen distribution for this study is the normal distribution. As maximum likelihood estimation of the random-parameter method is computationally complex, this study utilizes Halton draws. Halton draws have been proven to provide a more efficient distribution of draws for numerical integration than do purely random draws (Halton 1960; Train 2000; Bhat 2003).

Parameter and Model Significance

Marginal effects were used to interpret model results and determine the impact of an influential driver on an individual's WTP. The marginal effects measure the impact of a one-unit increase, when all others are held constant, of an independent parameter on WTP values. Indicator parameters are when one changes from zero to one. The marginal effects for indicator parameters is calculated as follows (Greene 2012):

$$\text{Impact} = E[y_i \mid \boldsymbol{X_i^1}] - E[y_i \mid \boldsymbol{X_i^0}] \quad (4)$$

, where $E[y_i \mid \boldsymbol{X}_i^1]$ is the estimated WTP when indicator variable $\boldsymbol{X}_i$ takes on value 1 and $E[y_i \mid \boldsymbol{X}_i^0]$ is the estimated WTP when indicator variable $\boldsymbol{X}_i$ takes on value 0.

To select the model with the best fit among the fixed and random-parameter Tobit models, researchers used the Akaike information criterion (AIC), where the smallest AIC indicated the best models for the data. The AIC is formulated as:

$$AIC = -2\log\left(\mathcal{L}(\hat{\theta}|data)\right) + 2K \quad (5)$$

, where $\log\left(\mathcal{L}(\hat{\theta}|data)\right)$ is a maximized log-likelihood function and K is the asymptotic bias correction term (Burnham and Anderson 2004).

Likelihood Ratio Test

Initial analysis of the survey data indicate that residents of shrinking cities were willing to pay more, on average, for improved water and wastewater LOS reliability in 2016 (94% and 93%, respectively) than they were in 2013 (77% and 71%, respectively). Still, a likelihood ratio test (LRT) was conducted to ensure that the two data sets should be modeled separately and that a statistically significant shift occurred in public perceptions (as measured by WTP). To conduct the LRT, a total of three random-parameter Tobit models (Eqns. 1 and 3) were fitted for both WTP for improved water LOS reliability and WTP for improved wastewater LOS reliability. One model was fitted for each individual dataset (e.g., 2013 and 2016) as well as for a combined dataset of WTP values from the 2013 and 2016 surveys. The LRT was applied to the three best models to determine whether the datasets should be modeled differently. The alternative hypothesis, H_a—that the two surveys are statistically different and should be modeled separately—was tested against the null hypothesis, H_o, that they were statistically similar. The LRT to test the hypothesis (Washington et al. 2011) is formulated as follows:

$$\chi^2 = -2\left[LL_{\beta_T} - LL_{\beta_{2013}} - LL_{\beta_{2016}}\right] \tag{6}$$

, where $LL(\beta_T)$ represents the log likelihood at convergence for the model from the combined 2013 and 2016 dataset, $LL(\beta_{2013})$ is the log likelihood at convergence for the model using only the 2013 data, $LL(\beta_{2016})$ is the log likelihood at convergence for the model using only the 2016 data, and χ^2 is a chi-square statistic with the degree of freedom being equal to the number of estimated parameters in the combined data set model subtracted from the total parameters in the 2013 and 2016 models.

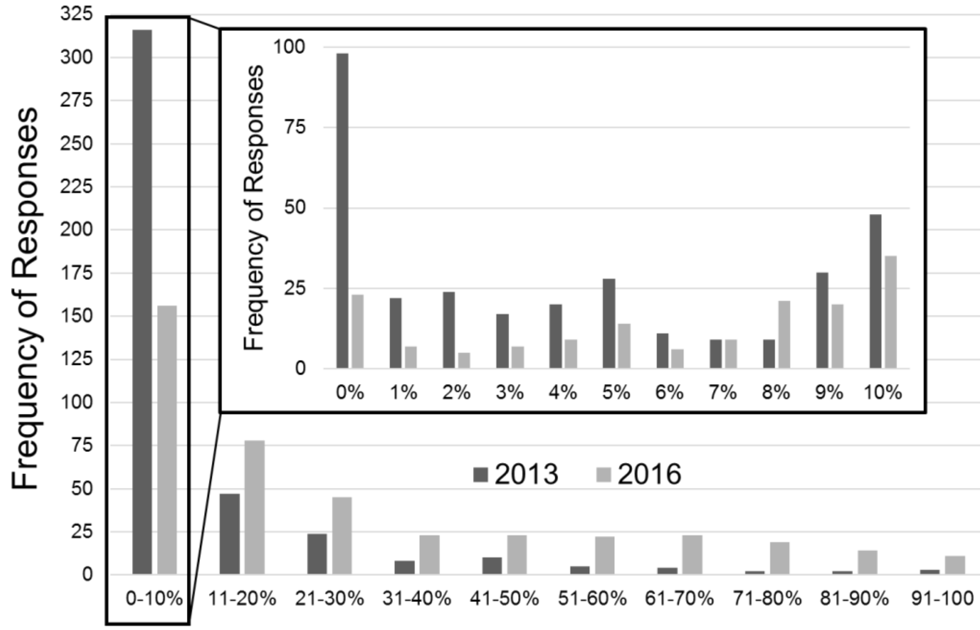
The models assessing the WTP for improved water LOS reliability resulted in a χ^2 statistic of 263.12 and 9 degrees of freedom, providing a confidence level exceeding 99.9%

that the 2013 and 2016 survey data are statistically different and should be modeled separately. Further, the models assessing the WTP for improved wastewater LOS reliability resulted in a χ^2statistic of 229.16 and 7 degrees of freedom indicating a confidence level of more than 99.9% that the 2013 and 2016 data should be modeled separately. The results of the LRT verify the temporal dynamic of public perceptions, for between 2013 and 2016 there was in fact a change in the WTP values of residents in shrinking cities for improved water and wastewater LOS reliability.

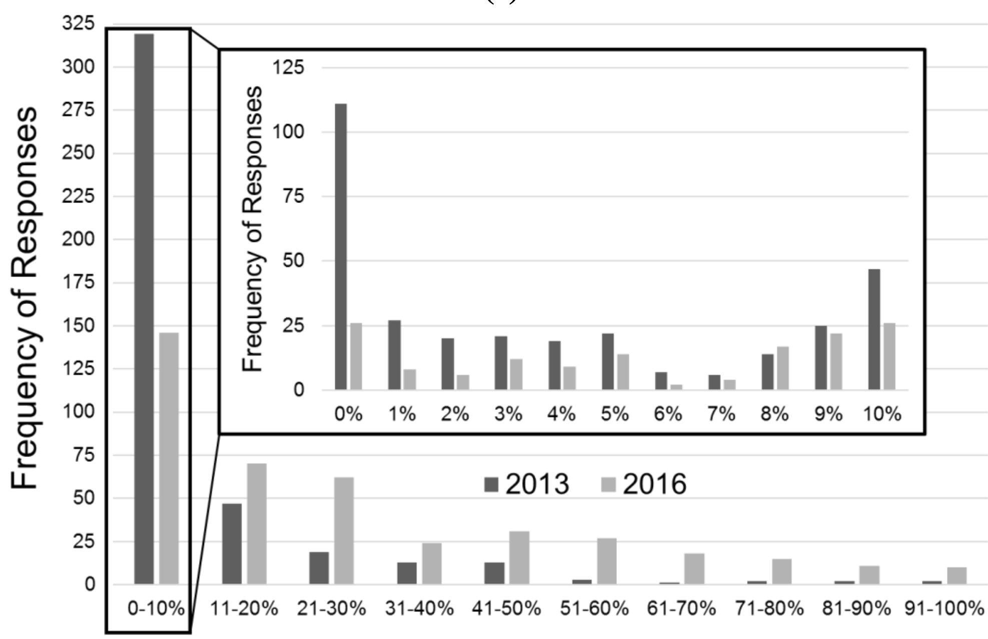
RESULTS

Survey Results

Figures 2a and 2b show the aggregated data regarding the residential WTP for improved water and wastewater LOS reliability. In 2013, respondents were willing to pay an average increase of 11% for water and 10% for wastewater LOS reliability improvements (Figure 2a). In 2016 (Figure 2b), it was found that respondents were willing to pay an average of 28% for improved water and wastewater LOS reliability (increases of 17% and 18%). Events that occurred after 2013 that may have contributed to this increase include the national water warning that prohibited residents of three Ohio and Michigan counties from drinking tap water due to the heavy toxin founds in Lake Erie (Satija 2014), the sewage overflow into city streets in NJ due to Superstorm Sandy (Schwirtz 2013), or the Flint Water Crisis (Yang and Faust, under review).



(a)



(b)

Figure 2**:** 2013 and 2016 WTP for improved reliability of (a) water service and (b) wastewater service

Figure 3 shows respondents' WTP for improved water and wastewater LOS reliability in 2013 (Figure 3a) and 2016 (Figure 3b). The figures illustrate the idea that a majority of respondents willing to pay for improved water LOS reliability (77% in 2013 and 94% in 2016) are also willing to pay for improved wastewater LOS reliability (71% in 2013 and 93% in 2016). Notably, an individual was more likely in 2016 than in 2013 to be willing to pay for *both* water and wastewater LOS reliability improvements (94% -- water vs. 93%--wastewater compared to 77% -- water vs. 71% -- wastewater).

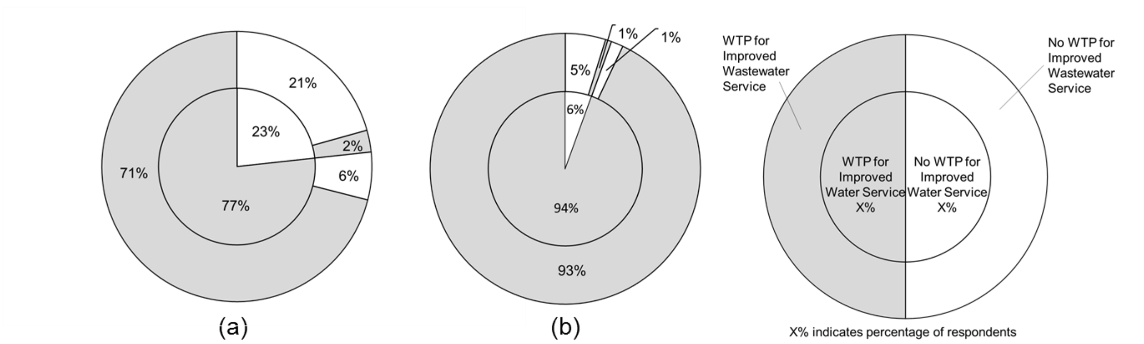


Figure 3: WTP for water and wastewater improved LOS reliability: (a) 2013 and (b) 2016 (percentage indicates percentage of respondents who are willing or not willing to pay an increase for LOS improvements)

Figure 4 shows the relationship between perceived increases/decreases (from 2013 to 2016) in quality and respondents' WTP. Significant in these figures is the increased number of respondents who perceived that their water quality had decreased from 2013 (Figure 4a) as compared to 2016 (Figure 4b). Attending this increase in perceptions of decreased quality is an increased WTP for improved water LOS reliability (i.e., 60 respondents in 2013 vs. 168 respondents in 2016).

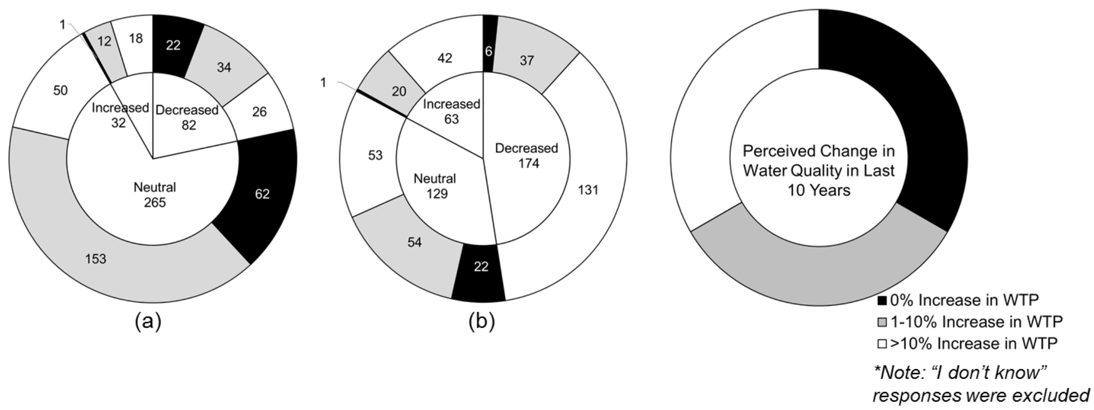


Figure 4: Frequency of responses that perceived change in water quality and respective WTP (i.e., 0%, 1-10%, >10%) for water LOS reliability improvements (a) 2013 and (b) 2016

Table 1 provides descriptive statistics of significant demographics identified in the 2013 and 2016 models.

Table 1. Select descriptive statistics from 2013 and 2016 survey

Parameters	Min/Max	2013 Ave (St. Dev)	2016 Ave (St. Dev)
Male (1 if male, 0 otherwise)	0/1	0.603 (0.490)	0.317 (0.466)
Age (1 if between 18-35, 0 otherwise)	0/1	0.290 (0.454)	0.610 (0.488)
Marital Status (1 if single, 0 otherwise)	0/1	0.356 (0.479)	0.437 (0.497)
Household Size (1 if single household, 0 otherwise)	0/1	0.216 (0.412)	0.144 (0.352)
Household Size (1 if household size greater than 2 individuals, 0 otherwise)	0/1	0.428 (0.495)	0.561 (0.497)
Education (1 if high school diploma is highest level of education, 0 otherwise)	0/1	0.347 (0.477)	0.326 (0.469)
Education (1 if college degree is highest level of education, 0 otherwise)	0/1	0.335 (0.473)	0.401 (0.491)
Employment (1 if employed or self-employed, 0 otherwise)	0/1	0.489 (0.500)	0.685 (0.465)
Income (1 if individual income between $0-$19,999, 0 otherwise)	0/1	0.242 (0.429)	0.193 (0.395)
Income (1 if individual income greater than $100,000, 0 otherwise)	0/1	0.040 (0.197)	0.164 (0.371)
Household Income (1 if household income between $0-$19,999, 0 otherwise)	0/1	0.150 (0.357)	0.115 (0.320)
Home Ownership (1 if own home, 0 otherwise)	0/1	0.496 (0.500)	0.656 (0.475)
Home Ownership (1 if first time home owner, 0 otherwise)	0/1	0.014 (0.119)	0.437 (0.497)
Home Ownership (1 if owned home 2 years or less, 0 otherwise)	0/1	0.667 (0.472)	0.645 (0.479)
Car Ownership (1 if household has 1 car, 0 otherwise)	0/1	0.451 (0.498)	0.399 (0.490)

Table 1. continued

Parameters	Min/Max	2013 Ave (St. Dev)	2016 Ave (St. Dev)
Car Ownership (1 if household has more than 2 cars, 0 otherwise)	0/1	0.093 (0.290)	0.126 (0.333)
Born in Current City (1 if born in city currently residing, 0 otherwise)	0/1	0.577 (0.495)	0.452 (0.498)
Urban (1 if perceiving to reside in an urban setting, 0 otherwise)	0/1	0.401 (0.491)	0.377 (0.485)
Michigan (1 if residing in Michigan, 0 otherwise)	0/1	0.112 (0.315)	0.153 (0.360)
New Jersey (1 if residing in New Jersey, 0 otherwise)	0/1	0.036 (0.186)	0.082 (0.275)
Ohio (1 if residing in Ohio, 0 otherwise)	0/1	0.335 (0.473)	0.251 (0.434)
Responsible for Bill (1 if responsible for water bill, 0 otherwise)	0/1	0.736 (0.441)	0.880 (0.325)

Random-Parameter Tobit Model Results

To assess the accuracy of the random-parameter extension, researchers plotted the actual and predicted WTP values and determined the Pearson product moment correlation coefficients. As shown in Table 2 below, the random-parameter approach outperformed the fixed Tobit model for each of the WTPs for improved water and wastewater LOS reliability models. This finding shows that the random-parameter method captured a significant amount of heterogeneity among the observations and predicted more accurately WTP values than did the traditional Tobit model. Further, this finding validates the use of the random-parameter method in WTP analyses as it was shown to have an effective rate of prediction.

Table 2. Pearson Product Moment Correlation Coefficients for Fixed and Random-Parameter Tobit Models

Model	Survey Year	Fixed-Parameter Tobit Model	Random-Parameter Tobit Model
Water	2013	0.1926	0.9377
	2016	0.1911	0.9952
Wastewater	2013	0.2555	0.9018
	2016	0.1869	0.8697

Tables 3 and 4 show the statistically significant parameters found to impact, in 2013 and 2016, the likelihood of an individuals' WTP for improved water and wastewater LOS reliability improvements. While select parameters remained consistent—albeit their relative impact may have differed—between 2013 and 2016 (e.g., age and perceiving to reside in an urban area), it can be seen most differed, reflecting dynamic and temporal perceptions.

Table 3. Random-Parameter Tobit model results for WTP for improved water LOS reliability

Independent Parameters	2013 Parameter (t-stat.)	2013 St. Dev (t-stat)	2013 Marginal Effect	2016 Parameter (t-stat.)	2016 St. Dev (t-stat)	2016 Marginal Effect
Constant	9.166 (6.41)	*fixed*		11.721 (10.06)	*fixed*	
Male (1 if male, 0 otherwise)	-2.782 (-3.01)	*fixed*	-2.338	7.152 (10.00)	15.906 (26.81)	7.152
Age (1 if between 18-35, 0 otherwise)	5.931 (5.46)	18.828 (22.18)	4.984	9.549 (13.54)	*fixed*	9.548
Marital Status (1 if single, 0 otherwise)	-0.633 (-0.63)	5.299 (7.30)	-0.532	---	---	---
Race (1 if white, 0 otherwise)	---	---	---	-10.189 (-12.61)	*fixed*	-10.189
Household Size (1 if household size greater than 2 individuals, 0 otherwise)	---	---	---	6.23 (9.14)	14.434 (32.74)	6.232
Education (1 if college degree is highest level of education, 0 otherwise)	---	---	---	-2.136 (-3.16)	8.669 (17.41)	-2.136
Employment (1 if employed or self-employed, 0 otherwise)	---	---	---	5.254 (6.80)	*fixed*	5.254
Income (1 if individual income between $0-$19,999, 0 otherwise)	-0.111 (-0.10)	9.556 (11.07)	-0.093	---	---	---
Household Income (1 if household income between $0-$19,999, 0 otherwise)	---	---	---	10.181 (9.76)	*fixed*	10.180

Table 3. continued

Independent Parameters	2013 Parameter (t-stat.)	2013 St. Dev (t-stat)	2013 Marginal Effect	2016 Parameter (t-stat.)	2016 St. Dev (t-stat)	2016 Marginal Effect
Home Ownership (1 if first time home owner, 0 otherwise)	---	---	---	5.793 (8.37)	17.277 (34.06)	5.793
Home Ownership (1 if owned home 2 years or less, 0 otherwise)	0.919 (0.95)	1.058 (1.91)	0.772	---	---	---
Car Ownership (1 if household has 1 car, 0 otherwise)	2.884 (3.10)	*fixed*	2.424	---	---	---
Born in Current City (1 if born in city currently residing, 0 otherwise)	---	---	---	5.447 (7.92)	11.832 (24.47)	5.447
Urban (1 if perceiving to reside in an urban setting, 0 otherwise)	2.688 (2.77)	20.467 (28.81)	2.259	3.966 (5.71)	21.244 (38.77)	3.966
Michigan (1 if residing in Michigan, 0 otherwise)	---	---	---	0.442 (0.48)	17.769 (20.20)	0.442
Ohio (1 if residing in Ohio, 0 otherwise)	-2.519 (-2.56)	4.357 (5.89)	-2.117	---	---	---
Responsible for Bill (1 if responsible for water bill, 0 otherwise)	-3.552 (-3.60)	*fixed*	-2.985	---	---	---
Log-Likelihood at Zero		-1504.42			-1931.79	
Log-Likelihood at Convergence		-1440.76			-1866.07	
AIC		2915.50			3772.10	
Maddala R^2		0.261			0.253	
Number of observations		421			451	

**Note: All random parameters are normally distributed*

Table 4. Random-Parameter Tobit Model results for WTP for improved wastewater LOS reliability

Independent Parameter	2013			2016		
	Parameter (t-stat.)	**St. Dev (t-stat)**	**Marginal Effect**	**Parameter (t-stat.)**	**St. Dev (t-stat)**	**Marginal Effect**
Constant	7.467 (5.29)	*fixed*		12.990 (4.93)	*fixed*	
Male (1 if male, 0 otherwise)	---	---	---	3.704 (2.13)	*fixed*	3.518
Age (1 if between 18-35, 0 otherwise)	4.384 (3.72)	14.928 (16.74)	3.431	9.451 (5.49)	*fixed*	8.976
Race (1 if white, 0 otherwise)	---	---	---	-8.325 (-4.42)	*fixed*	-7.906
Race (1 if black, 0 otherwise)	3.822 (2.93)	*fixed*	2.991	---	---	---
Household Size (1 if single household, 0 otherwise)	-5.020 (-3.62)	*fixed*	-3.929	---	---	---
Household Size (1 if household size greater than 2 individuals, 0 otherwise)	---	---	---	3.837 (2.28)	8.951 (8.68)	3.644
Education (1 if high school diploma is highest level of education, 0 otherwise)	-2.115 (-1.95)	*fixed*	-1.655	---	---	---
Employment (1 if employed or self-employed, 0 otherwise)	---	---	---	4.564 (2.47)	*fixed*	4.334
Income (1 if individual income greater than $100,000, 0 otherwise)	---	---	---	6.941 (3.10)	*fixed*	6.592
Home Ownership (1 if own home, 0 otherwise)	-0.420 (-0.39)	1.906 (2.64)	-0.329	5.793 (8.37)	17.277 (34.06)	5.793

Table 4. continued

Independent Parameter	2013 Parameter (t-stat.)	2013 St. Dev (t-stat)	2013 Marginal Effect	2016 Parameter (t-stat.)	2016 St. Dev (t-stat)	2016 Marginal Effect
Home Ownership (1 if first time homeowner, 0 otherwise)	---	---	---	3.378 (1.98)	12.710 (10.07)	3.208
Car Ownership (1 if household has 1 car, 0 otherwise)	4.203 (3.85)	*fixed*	3.289	---	---	---
Car Ownership (1 if household has more than 2 cars, 0 otherwise)	---	---	---	-10.586 (-3.69)	*fixed*	-10.054
Born in Current City (1 if born in city currently residing, 0 otherwise)	---	---	---	7.797 (4.62)	7.224 (6.09)	7.405
Urban (1 if perceiving to reside in an urban setting, 0 otherwise)	3.128 (2.79)	20.129 (25.81)	2.448	5.484 (3.22)	20.463 (15.46)	5.209
New Jersey (1 if residing in New Jersey, 0 otherwise)	---	---	---	9.434 (3.21)	14.604 (5.17)	8.960
Ohio (1 if residing in Ohio, 0 otherwise)	-0.343 (-0.31)	5.349 (6.78)	-0.269	---	---	---
Responsible for Bill (1 if responsible for water bill, 0 otherwise)	-3.985 (-3.43)	*fixed*	-3.119	---	---	---
Log-Likelihood at Zero		-1443.31			-1866.48	
Log-Likelihood at Convergence		-1383.82			-1807.67	
AIC		2797.80			3651.30	
Maddala R^2		0.246			0.230	
Number of observations		421			451	

**Note: All random parameters are normally distributed*

DISCUSSION

Model results reveal that between 2013 and 2016 certain geographic and sociodemographic parameters impacted individuals' WTP for improved water or wastewater LOS reliability. This finding suggests that public perceptions, as measured by stated WTP, may change over time. This underscores the assertion above that the temporal nature of public perceptions can influence the success or failure of infrastructure policies and projects (Lorenzoni et al. 2007; West et al. 2010; Leung et al. 2013). Infrastructure projects have an average duration of 13 years, so public support or opposition towards a project can vary considerably and influence its outcome (Flyvbjerg et al. 2004). Using the results from this study, decision makers can use times of greater public WTP as opportunities to implement capital projects and increase operational revenues. Moreover, cities can focus on the influential parameters of WTP that changed over time to develop marketing and outreach strategies that sustain and garner public support and prevent opposition.

To determine whether WTP changed between 2013 and 2016 within a certain state, researchers tested state-level geographic parameters for significance. This allowed for the examination of possible events within (or proximal to) a state that may have caused this shift in WTP perceptions. Further, more accurate inferences were made possible by assessing geographic parameters at the state level, as this narrowed the number of possible events that may have caused a shift in WTP perceptions. City-level parameters were also tested during analysis, but none were found to be significant in either water or wastewater models. The lack of significant city-level parameters may indicate that many of the local issues and challenges may have regional impacts on public perceptions (e.g., Flint Water Crisis). From the final models, the influence of state-level geographic parameters (Ohio, Michigan, and New Jersey) on WTP were found to be statistically significant and to have changed over time. The discussion below of the significant state-level geographic parameters suggests that public opinion can be driven by a respondent's proximity to events (Sackett and Botterill 2006; Zielinksi-Gutierrez and Hayden 2006; Brody et al. 2008; Milfont et al. 2014). This finding is consistent with previous studies that have shown that public perceptions change as a result of events proximal to respondents' cities (Sackett and Botterill 2006; Zielinksi-Gutierrez and Hayden 2006; Brody et al. 2008; Milfont et al. 2014).

In the 2013 water model, the state of Ohio geographic parameter was found to be statistically significant, but in the 2016 model it no longer was (Table 3). In 2013, approximately 72% of Ohio's shrinking city residents were less likely to be willing to pay for increased water rates while approximately 28% were more likely. Between 2013 and 2016, water rates in Ohio increased by an average of 3.3%, greater than the national inflation rate (EPA 2014). The change in consumer price index (CPI)—a measure of the average price of consumer goods—from the previous year was 1.4% and 0.8% in 2013 and 2016 (EPA 2014). In other words, the cost increase in consumer goods from the previous year was less in 2016 than 2013. This decrease may explain why, in 2013, a majority of residents were less likely to express WTP for increased water rates. This finding supports the idea that public perceptions and WTP can fluctuate, influenced by external events. Hence, gaining a grasp of public sentiment may be done more efficiently with something that goes beyond a single cross-sectional assessment. Indeed, periodic assessments of public opinion and WTP may provide valuable information to decision makers. The periodic accounting of public perceptions could allow for some decisions to stand that may, at another time, have failed. Or, in contrast, decision makers may be able to identify proactive actions that could ameliorate public opposition.

Similarly, the State of Michigan geographic parameter was found to be statistically significant only in the 2016 water WTP model (Table 3). In 2016, slightly more than half (51%) of Michigan residents of shrinking cities were more likely to be willing to pay for improved water LOS reliability. In 2014, as construction was underway for a new pipeline to deliver water from Lake Huron to the City of Flint, Flint sourced their water from the Flint River, resulting in hazardous levels of lead in the public drinking water system, affecting nearly 100,000 Flint residents (CNN Library 2017). Lead exposure and abnormal consumption of lead can lead to significant health issues that affect the heart, kidneys, and nerves. In children, exposure to lead increases the risk of impaired cognition and behavioral disorders (CNN Library 2017; WHO 2017). As a result, multiple lawsuits, including class action lawsuits, were filed by Flint residents against Michigan, the City of Flint, and several state and city officials. As of March 2018, residents were still being instructed to utilize bottled or filtered water until all lead pipes in the city had been replaced, which, per a court settlement, must be completed by 2020 (CNN Library 2017).

The distribution of the two surveys straddled this event, known as the Flint Water Crisis. This fact may explain the statistical significance of this parameter changing from insignificant to significant—with more than half of Michigan residents living in shrinking cities expressing an increased likelihood of WTP for improved water LOS reliability. These residents may have been directly affected by the Flint Water Crisis (or have lived within its proximity) and may be now more willing to pay increased water rates to prevent a similar situation from occurring in other parts of Michigan and to restore the Flint water system to pre- Flint Water Crisis conditions. Previous studies (e.g., Sackett and Botterill 2006; Zielinksi-Gutierrez and Hayden 2006; Brody et al. 2008; Milfont et al. 2014) have supported the idea that public perceptions can be affected by proximal events.

Regarding significant geographic parameters for the wastewater model, the states of New Jersey and Ohio were found to be statistically significant. The Ohio parameter was significant and randomly distributed in the 2013 wastewater model, but not in 2016. As noted above, the cost increase in consumer goods in the State of Ohio from the previous year was less in 2016 than in 2013. This decrease may explain why the Ohio parameter was not significant in 2016. Conversely, the New Jersey parameter was not significant in 2013, but was significant in 2016. In late 2012, the aftermath of Superstorm Sandy sent 10 billion gallons of raw sewage into waterways and New Jersey streets (Schwirtz 2013). The storm exposed the faults in the aging wastewater infrastructure and submerged entire sewage plants (New Jersey 2012). This resulted in millions of dollars in losses, forcing the state senate to act on improving the states wastewater systems through Senate Bill S-762 in 2016 (217th Legislature 2016). The complete extent of the damage wasn't reported by FEMA until late 2013, which could provide an explanation for why the New Jersey parameter wasn't significant in 2013, but was in 2016 (FEMA 2013). The public's awareness of these happenings in their surroundings could provide an explanation for the WTP for improved wastewater LOS reliability in New Jersey.

This discussion on significant state-level geographic parameters suggests that public perceptions, as measured by WTP, may be event-driven. Decision makers can present case studies to the public that show that failure to proactively manage infrastructure systems may lead to catastrophic failures. To obtain public support, however, decision makers must not rely on external events to occur in their jurisdiction. Indeed, decision makers can continually leverage sociodemographic factors to hamper opposition and sustain or garner public support. For instance, decision makers can gain public support by utilizing the factors that influenced a favorable change in WTP perceptions among certain age groups. By tailoring marketing strategies to these favorable factors, utility managers can help influence public perceptions of infrastructure projects and policies. Of the sociodemographic parameters that were revealed by the statistical models, the following discussion examines those that have changed between 2013 and 2016 to understand why the change may have occurred.

In all the models, participants who perceived that they resided in a location classified as urban had an increased likelihood of WTP for improved water and wastewater LOS reliability. Prior to the shrinking classification, the majority of shrinking cities were large urban metropolises (Pallagst 2009). Prior to their decline, all shrinking cities in this study peaked at approximately 100,000. In 2013 and 2016, however, only 40.1% and 37.7% of respondents perceived themselves to be situated in an urban setting (Table 1). In addition, the results indicate that those born in their residing city were more willing to pay for improved water and wastewater LOS reliability in 2016. This statistic could be capturing individuals with strong place attachment who are often more willing to adapt to changes and are proven to be more willing to engage in public issues (Giuliani 2003; Lewicka 2011). This place attachment is possibly captured in the 2016 model results, which show a decrease from 2013 to 2016 in respondents indicating that they were born in the city where they currently reside (57.7% vs. 45.2%).

In both the WTP for improved water and wastewater models, parameters referring to respondents who owned their homes for two years or less, or who reside in a household with two or more persons were insignificant in 2013 but significant in 2016. The finding that a majority of individuals owning a home were more likely to express WTP for improved water and wastewater services suggests an established long-term residency with their city. This is supported by prior research showing that long-term collaborative relationships between utilities and customers lead to heightened trust between the two (Humphries and Wilding 2004). Further, households with two or more persons had an increased likelihood of WTP for improved water and wastewater LOS reliability improvements within shrinking cities. This finding may be capturing dual-incomes within the households that contribute to the monthly utility budget. Service bills proportionally impact low incomes more than high incomes (Pallagst 2009; Faust et al. 2016b), therefore respondents with higher total household incomes feel better equipped to shoulder the burden of increased utility rates.

Between 2013 and 2016, respondents between 18 and 35 years of age also had a statistically significant shift in perception regarding WTP for improved water and wastewater LOS reliability. Today, younger generations show a greater use of social media and blogs, which are sources of a variety of news and information (Holt et al. 2013; Associated Press 2015; Pew Research Center 2018). As Bakker and de Vresse (2011) found, younger populations that take advantage of the ease of information accessibility often leads to more civic engagement; one result of such participation may be an increase in WTP. The increasing engagement with social media, and the ease of information accessibility may explain the positive shift among 18- to 35-year-olds in WTP for improved water and wastewater services. Additionally, engagement in civic activities to cope with community issues increases as more people use social networking as their primary news source (Gil de Zúñiga et al. 2012). In this study, the percentage of respondents who indicated that social media was their primary news source increased by 11% between 2013 (16%) and 2016 (27%). Utility managers and decision makers may choose to use social media as a platform to convey their messages regarding infrastructure projects and policies to sustain and garner public support.

Past studies have shown that residents of lower incomes are willing to pay increased rates for improved water LOS reliability (Knetsch 1990; Whittingtone et al. 1990; Faust et al. 2016b; Faust et al. 2018). This study is consistent with that finding, as respondents with lower household incomes (i.e., \$0 - \$19,999) were statistically insignificant in the 2013 water model but statistically, and positively, significant in the 2016 model. This shift in perceptions may be capturing a perceived decrease in quality of service within shrinking U.S. cities following the aforementioned media events and proximity to these events translating into an increased WTP, as shown in Figure's 4a and 4b. This parameter states that even households whose incomes are below poverty level (\$24,563 for family of four; U.S. Census Bureau 2016) are willing to pay for improved water LOS reliability in shrinking cities following the perceived decrease in the quality of their water.

In summary, descriptive statistics suggest that, on aggregate, the WTP of residents in shrinking cities, changes over time. Cities with limited money and resources for maintenance and capital investment may benefit from using the parameters identified in this study to develop strategies (e.g., outreach programs, targeted education, media advertisements) to target specific sociodemographic or geographic groups. This targeted outreach can result in increases to their revenue streams due to shifting perceptions of respondents' stated WTP. Specifically, using the sociodemographic parameters as opportunities for educating portions of communities on the benefits of capital investments as a way of increasing public support for infrastructure projects. Similarly, using the geographic parameters may also present an opportunity to implement infrastructure projects and increase operational revenue due to higher WTP by residents resulting from a change in the built environment (e.g., events).

SUMMARY AND CONCLUSIONS

This study sought to assess the temporal dynamics of public perceptions as they relate to WTP for improved water and wastewater LOS reliability in 21 shrinking cities of the U.S. and to investigate the shifts in geographical and sociodemographic parameters that influence this stated WTP. The results of the LRT demonstrate that responses to the 2013 and 2016 WTP questions were statistically different, reflecting a measurable shift that occurred in WTP between 2013 and 2016. Results of the random-parameter Tobit model also indicate that geographical and sociodemographic parameters that influence WTP shifted at some point between when the two surveys were administered. For example, the parameter capturing residents located in shrinking cities in Michigan and New Jersey revealed shifts in WTP for improved water (Table 3) and wastewater (Table 4) LOS reliability. Many factors may have contributed to this shift, including being in the proximity of events (e.g., Sackett and Botterill 2006; Zielinksi-Gutierrez and Hayden 2006; Brody et al. 2008; Milfont et al. 2014; the Flint Water Crisis or aftermath of Superstorm Sandy), new information (e.g., increased social media usage), or the economic state of the community. Further, increased usage of social media between 2013 and 2016 may have been a factor in the increase in WTP for improved water and wastewater LOS reliability among respondents between the ages of 18 and 35 (Tables 3 and 4). Because of this shift in perceptions, the public engagement processes should be continuous and conducted periodically throughout the lifecycle of projects and policies, thus ensuring that public opinion is adequately being captured. In the example of Portland, had the residents of the city not pursued a second time the infrastructure tax, they would likely have missed that opportunity for revenue generation (Njus 2016). To reduce the costs of collecting it, public perception data can be conducted on a regular basis (e.g., annually) rather than continually (Yang and Faust, under review). The results of such analysis can help utility managers and project managers in fiscally strained environments identify periods of public support to introduce infrastructure projects and policies.

This study, in measuring WTP for improved water and wastewater LOS reliability improvements, demonstrates and assesses the temporal nature of public perceptions, and introduces the use of the random-parameter Tobit modeling approach in analyzing stated WTP in shrinking cities. This temporal nature was captured through the application of the random-parameter Tobit model, which determined changing geographic (e.g., state-level) and sociodemographic (e.g., income, age, household size, residential area) drivers of respondents WTP. Due to the inherent limitations of survey data and WTP studies, the statistical model used in this study accounted for unobserved heterogeneity and protest zeros by allowing estimable parameters to vary across individuals and censoring WTP responses at zero. As measured by the Pearson product moment correlation coefficient, the random-parameter approach was found to be superior over the standard Tobit model, indicating that capturing unobserved heterogeneity is necessary to more accurately predict WTP values (Table 2). As it has been shown to produce better WTP predictions, this study suggests that the random-parameter method may be employed in WTP studies that assess parameters with inherent variation (e.g., geographical). Further, the results of the random-parameter Tobit model verify that a majority of geographic and sociodemographic parameters affecting WTP perceptions are heterogeneous and vary across the population (Tables 3 and 4). Moreover, respondents' perceived water quality also changed during the 3-year span assessed in this study (Figure 4).

Overall, the findings of this study determine that public perceptions are indeed dynamic and model results present an opportunity for enhanced collaboration amongst utility leaders and the public. As noted above, surveys cannot capture all possible information about an individual's perception or attitude. However, decision makers can deploy future surveys to gather more specific information tailored to their needs and utilize the methods presented in this study for accurate results and interpretations. Continuing to understand the dynamic of public perceptions can create utility management techniques that are feasible for both shrinking and non-shrinking cities resulting in sustainable infrastructure systems.

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